Air pollution and post-COVID-19 work resumption: evidence from China

Yu Zheng¹

Received: 27 May 2021 / Accepted: 25 September 2021 / Published online: 16 October 2021
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2021

Abstract

To cope with the coronavirus disease (COVID-19), national or sub-national regions have carried out many powerful anti-pandemic measures such as locking down, which may improve their regional air quality. This paper examines the relation between regional air pollution and work resumption from a novel post-pandemic perspective. Using a unique panel dataset on China's detailed industrial electricity consumption, this paper does not find a positive relation between post-COVID-19 work resumption and regional air pollution during China's early-stage recovery. This result is obtained after controlling for province and date fixed effects, as well as local weather conditions. However, the positive relations are found in a particular sub-sample of large industrial enterprises and a particular sub-sample of April. These findings indicate that large industrial enterprises may recover first, and the resumption is progressing gradually. Finally, several policy implications are provided, which are essentially helpful for other countries' post-pandemic recovery.

Keywords Post-COVID-19 · Air pollution · Work resumption · Electricity consumption · Coronavirus recovery · China

Introduction

To contain the COVID-19, a global public health crisis indeed (Wang et al. 2020), so many countries or regions have adopted various effective counter-virus measures to reduce person-to-person interaction, e.g., restricting transportation (private or public), encouraging social distancing, and even locking down cities (like China). Notwithstanding that the cost of these defensive measures is so huge, these measures still could bring some substantial social benefits (He et al. 2020). More specifically, environmental quality (air Collivignarelli et al. 2020; Dantas et al. 2020; He et al. 2020; Kanniah et al. 2020) or water (Yunus et al. 2020) improvement and the resulting health benefits (Chen et al. 2020) may to some extent offset the cost of these anti-pandemic measures.

Unlike previous studies using data before or during the pandemic (Dang and Trinh 2021; Khomsi et al. 2021;

Wang et al. 2021), this study creatively makes full use of a confidential official dataset to examine the relation of the COVID-19 and local air pollution from a “post-pandemic”¹ perspective. That is, the local disclosure of the data on post-pandemic work resumption gives us an excellent opportunity to conduct this study. Hence, the core question is whether or not the rapid work resumption in a post-pandemic short-window period has pushed up or restarted the ambient air pollution, and how this impact differs in the aspects of enterprise size and time evolution.

The null hypothesis of this study is that the early-stage post-COVID-19 recovery has a negative effect on local air quality after controlling the impact of other confounding factors. This may arise because the post-COVID-19 recovery reverses the unintended anti-pandemic improvement of air quality (Dang and Trinh 2021; Kumar et al. 2021; Wang et al. 2021). The empirical analyses use a comprehensive dataset at the province-by-day level from March 3rd to April 21st in 2020. In particular, this study matches the official post-COVID-19 recovery data² provided by the China Southern Power Grid (CSG) to the air quality data collected

Communicated by Lotfi Aleya.

✉ Yu Zheng
cnyuzh@163.com

¹ State Key Laboratory of Pollution Control & Resource Reuse, School of Environment, Nanjing University, Nanjing 210093, People's Republic of China

¹ This is a relative concept, which in this study mainly refers to the work resumption activities after the pandemic.

² I use the industrial electricity consumption in this study as a proxy for the post-COVID-19 recovery.

from the Ministry of Ecological Environment (MEE) and then constructs a panel consisting of 250 province-dates. Using fixed-effect panel regressions, this study finds no positive relation between the post-pandemic recovery and ambient air pollution so that rejecting the null hypothesis. The results are obtained after controlling for province and date fixed effects, as well as local weather conditions.

In addition, two various heterogeneous analyses are conducted from the perspective of enterprise-level characteristics and time evolution. Interestingly, the positive relations are found in a particular sub-sample of large industrial enterprises (LIEs) and a particular sub-sample of April. On the one hand, these findings indicate that China's LIEs have undergone a remarkable recovery, hence no doubt throw a knock-down counterpunch to some news on China's faking recovery (Krawczyk 2020; Yuan Ruiyang 2020). These findings also suggest the success of China's powerful package of stimulating policies, as well as the wisdom of the street-stall and small-store economy. On the other hand, nearly all coefficients in the sub-sample of April transform into positive relative to those in the sub-sample of March, which implies that China's domestic economy is gradually recovering over time. Furthermore, several additional tests are conducted to validate the robustness of the main results, mainly including substituting the measure variable of post-COVID-19 recovery by the resumption rate (RR), adjusting the study sample, using the substitutable model settings, and the weighted average air and weather data based on city land area. Overall, the core findings are insensitive to various robustness checks. Finally, a few policy implications are provided regarding other countries' post-pandemic recovery.

China provides an ideal setting to test the hypothesis for two reasons. First, it is the first country afflicted with the COVID-19, and also the first one to embark on the work resumption. This work provides an indirect evaluation of China's public management policy during the post-pandemic era, which has received much attention from academics, industry representatives, and policymakers. Second, China is facing to some extent severe air-pollution problems, and more importantly, it has been quantified the air quality improvements result from the COVID-19 outbreak in recent studies (e.g., Chen et al. 2020; He et al. 2020).

This study sheds new light on the recent hot spots of the literature on the environmental impacts of public health shocks (such as COVID-19). The contribution of this paper is threefold. First, although many existing studies have found that the COVID-19 has decreased ambient air pollution to some extent (Dang and Trinh 2021; Khomsi et al. 2021; Wang et al. 2021), the existing methods analyze data collected during (or before) the pandemic without exception. Instead, this paper uses the post-COVID-19 work resumption data

for re-examination, thus enriching the strand of literature on examining the relation between public health events (such as the pandemic) and air quality. To my best knowledge, this is among the first in the literature to investigate the influence of the COVID-19 on air quality from a post-pandemic perspective. Second, from the perspective of economic development, the empirical results of this paper can not only provide an indirect evidence of China's powerful policy package on stimulating recovery but also provide policy implications for other countries that are struggling to find a solution to their domestic economic recovery. Third, this paper also contributes to the branch of literature on post-pandemic economic recovery. The current studies on post-COVID-19 economic recovery are relatively lacking. Thanks to its unique political advantage, China is the only major global economy to realize post-COVID-19 economic recovery (Kuo 2020). Thus, making full use of China's official post-COVID-19 electricity data, this study bridges this knowledge gap to some extent.

The remainder of this paper is organized as follows. The following section "Pandemic lockdown, work resumption in China" provides the background on China's virus containment as well as the status of post-pandemic recovery. The "Data and method" section describes the data and discusses the variables and empirical strategy. Empirical findings are presented in the "Empirical results" section. The last section concludes.

Pandemic lockdown, work resumption in China

The rapid and widespread COVID-19 has had an immeasurable impact on China, the country with the second-largest economy and the largest population in the world. A rich set of regulations are implemented to counter the COVID-19, among which the policy of locking down cities is one of the most cost-effective and initiative. This section briefly reviews the outbreak of COVID-19, preventive measures, and the work resumption in China. More visually, the timing of China's anti-COVID-19 is mapped in Fig. 1.

In December 2019, an unknown virus, later known as COVID-19, emerged in Wuhan, China (Lu et al. 2020; Zhu et al. 2020). After being aware of the person-to-person transmission of the virus, China's central government took the quick measure of locking down Wuhan to prevent its further spread on January 23, 2020. This may be because China has learned valuable lessons from its 1911 battle against the pneumonic plague in Manchuria. With the exponential growth of confirmed cases, however, many

Fig. 1 Timing of China's anti-pandemic. *Notes:* Compiled by the author from publicly available figures. The sample period is from March 3rd to April 21st of 2020, to capture the effect, impact, and heterogeneity of the initial work resumption in China

other cities have begun to announce the implementation of closed management.³

There is no doubt that the pandemic outbreak has caused an unprecedented blow to the global major economies, including China. Thanks to China's unique political ecology, her rapid powerful enforcement of a battery of anti-pandemic measures featuring the city locking down has yielded such great success that the pandemic has then gradually receded, even though China was one of the most affected economies in the early. Hence, with the effective control of the pandemic, restarting the economy becomes particularly pivotal to China's central government. One week after the Chinese Spring Festival holiday, on 10 February 2020, many regions in China began resuming work, including the south-five provinces. The initial phase of work resumption is, however, relatively slow. Furthermore, due to the data availability, the time frame of this paper is from March 3rd to April 21st in 2020. Basically, anti-epidemic measures, especially the locking down, have had a significant impact on people's daily lives, work, sleep health, civic culture, etc. (Beck et al. 2021; Crossley et al. 2021; Durante et al. 2021; Engzell et al. 2021; Hensvik et al. 2021). Thus, the post-pandemic economy must bounce back as soon as possible. As a result of its innovative public management policies, China has taken a leading role in resuming work and is achieving remarkable results among major economies.

Data and method

This section mainly profiles the data and introduces the model set. On the one hand, this paper integrates a unique dataset composed of three types of data, i.e., the local air quality data, the official work resumption data, and the local weather data. On the other hand, the main variables used and the empirical model are described in detail.

Data

To comprehensively study the influence of the COVID-19 pandemic (as discussed above, here mainly refers to “post-COVID” work resumption) on regional air quality and its impact mechanism, this paper synthesizes multiple sets of statistical data and finally construct a unique confidential dataset at the province level with data for nearly 2 months (from March 3rd to April 21st of 2020). In particular, for the main empirical analyses, the comprehensive database principally includes the city-by-day air quality data, the province-by-day official statistical data for electricity consumption of industrial enterprises, and the city-by-day weather data. The details are as follows.

First, the urban air quality data—the main outcome variables in this paper—derives from the Ministry of Ecological Environment (MEE). Since 2001, the Ministry of Environmental Protection (MEP, reorganized to MEE in March 2018) has begun to officially disclose the daily air pollution data, which to some extent is also considered to be the beginning of the Chinese government's attention to its environmental issues. This daily indicator disclosed officially by the MEP is the Air Pollution Index (API). Since 2013, however, a more detailed renewed indicator—Air Quality Index (AQI)—has replaced the original API, which comprehensively considers the monitoring concentrations of six main air pollutants (i.e., SO_2 , NO_x , CO , O_3 , PM_{10} , and $\text{PM}_{2.5}$) and consistent with the calculation formula of AQI in the USA. The AQI monitoring data set is the most comprehensive, effective, and real-time official air quality data that reflects China's air quality, which has been widely used by a battery of researchers (see, e.g., Li et al. (2018), H. Liu et al. (2017), Luo et al. (2020), and Tong et al. (2016)).

Second, the official province-by-day panel data set on the electricity consumption of industrial enterprises primarily derives from the China Southern Power Grid (CSG), one of the big two state-owned power grid enterprises in China. More specifically and accurately, this top-secret data was provided by the CNAO's Guangzhou Resident Office via a confidentiality deal, one of whose main responsibilities is to audit the operation of China's central enterprises including the CSG. After verification by the CNAO's Guangzhou

³ As of 12 February 2020, a total of 207 cities have taken measures of locking down cities (wiki on COVID-19 pandemic lockdown in Hubei, accessed 03 October 2020); https://en.wikipedia.org/wiki/COVID-19_pandemic_lockdown_in_Hubei

Resident Office, this data set is more convincing, which provides an excellent opportunity to study the transmission mechanism behind the relation between the post-COVID-19 work resumption and the variations in local air quality.

Third and finally, the data on weather conditions at the city level—the main control variables in this paper—is collected from the National Climate Data Center, which is affiliated with the National Oceanic and Atmospheric Administration (NOAA). This study considers various weather variables, including the dew point temperature, wind speed rate, air temperature, and sea level pressure. Finally, we merge these three data sets to the province-day level. And one should note that the average values of city-by-day of air quality and weather data for each province are calculated to match the province-by-day industrial electricity consumption data.

Variables and description

Dependent variables

As mentioned above, some previous studies have investigated the causation or correlation between ambient air pollution (or quality) and the pandemic lockdown (or halting production). This paper, however, focuses on the influence of post-pandemic recovery on air quality. Realized this, following the method of other studies (Dang and Trinh 2021; Khomsi et al. 2021; Wang et al. 2021), this paper takes seven main indicators of air quality as the dependent variables. More specifically, the natural logarithm of Air Quality Index (AQI), fine particulate matter (diameter ≤ 2.5 microns ($PM_{2.5}$) and diameter ≤ 10 microns (PM_{10})), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO) are used as the measures of the air quality. It is worth noting that, the lower the AQI, the higher the air quality; while the lower the other six indicators, the lower the air quality. At the same time, the ambient AQI is calculated based on the other six indicators following the technical regulation promulgated by the MEE.⁴ Unlike some other studies, however, this work not only includes the AQI but also includes the six other indicators. Taking into consideration of the calculation rules of AQI and China's environmental context, more attention to the PM has been paid compared to the other pollutants, while the results of all six pollutants are provided in this study.

Independent variables

Notwithstanding that a rich data set on China's post-pandemic work resumption is provided by the CNAO's

Guangzhou Resident Office, two key indicators on the industrial electricity consumption are mainly focused on because of reflecting the economic recovery directly. More specifically, the province-by-day total daily electricity consumption of industrial enterprises (ELE)⁵ is used as the barometer of industrial enterprises' recovery in the baseline models. Meanwhile, this paper also constructs a proportional index—the enterprise's resumption rate (PR)—as an alternative measure in the “Robustness checks” section. The PR equals the ELE divided by the average daily electricity consumption in December 2019. Obviously, the higher the two values, the better the degree of work resumption of enterprises in the corresponding province. Generally speaking, the electricity consumption is more proper as the measure of the work resumption than any other indicators such as back-to-work persons, since it directly links to the production activities. Another reason is that some other statistical indicators are rough enough when counting whether one factory has resumed work. For instance, even if only one or two persons return to work, it is considered that the factory has resumed work in some cases. So, the other indicators are abandoned and the more effective indicator of electricity consumption is chosen as the measure of work resumption in this study.

Control variables

To control the confounding influences of any other factors on the ambient air quality, this paper introduces two types of control variables. On the one hand, several studies contend that weather conditions can affect the ambient air quality (see, e.g., Clancy et al. (2002), Cropper et al. (1997), Kelsall et al. (1997), and Zhong et al. (2021)). Thus, the weather conditions (Weather) are controlled in the empirical models, mainly including the air temperature (AT), dew point temperature (DPT), sea level pressure (SLP), wind direction (WD), and wind speed rate (WSR). On the other hand, the thermal power generation in which coal-fired power generation accounts for a large proportion may also confound the regressions (Du et al. 2020; Sheehan et al. 2014; Yuan et al. 2018). Hence, the province-month-level thermal power generations (TPG) are included in the empirical models.

Descriptive analysis

Table 1 shows a brief description of the main variables, its acronyms used in the analysis, main summary statistics, and the number of observations for the total sample. From the descriptive statistics, one could easily get the following preliminary findings. First, the province-daily electricity

⁴ Refer to https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/t20120302_224166.shtml.

⁵ Actually, the natural logarithm of ELE ($\ln(ELE)$) is used in the baseline models.

Table 1 Summary statistics and description of variables

Variables	Obs	Mean	S.D	Variables	Obs	Mean	S.D
ln(ELE)	250	9.980	1.117	ln(NO ₂)	250	2.802	0.405
(province-daily electricity consumption of enterprises, 10,000 kWh)				(nitrogen dioxide)			
ln(ELE_L)	250	9.632	1.292	ln(O ₃)	250	4.480	0.359
(province-daily electricity consumption of LIEs, 10,000 kWh)				(ozone)			
ln(ELE_G)	250	8.500	1.085	ln(CO)	250	-0.418	0.221
(province-daily electricity consumption of GIEs, 10,000 kWh)				(carbon monoxide)			
PR	250	73.1	13.6	ln(WSR)	250	3.243	0.339
(enterprises' resumption rate, %)				(wind speed rate, m/s)			
ln(AQI)	250	3.752	0.432	ln(AT)	250	5.193	0.251
(air quality index)				(air temperature, °C)			
ln(PM _{2.5})	250	3.152	0.514	ln(DPT)	250	4.782	0.496
(fine particles, designated PM _{2.5} , with a diameter of 2.5 μm or less)				(dew point temperature, °C)			
ln(PM ₁₀)	250	42.34	17.09	ln(SLP)	250	9.147	0.0530
(inhalable coarse particles, designated PM ₁₀ , which are coarse particles with a diameter of 10 μm or less)				(sea level pressure, hPa)			
ln(SO ₂)	250	1.981	0.467	ln(TPG)	250	4.266	0.917
(sulfur dioxide)				(province-month-level thermal power generation, 100 million kWh)			

Notes: The unit of observation is the province-day. Data source: The information on post-pandemic recovery comes from the CNAO's Guangzhou Resident Office; data on air quality and weather are from the Ministry of Ecological Environment (MEE) and the National Climate Data Center of NOAA, respectively.

consumption of LIEs is not surprisingly even larger than that of general industrial enterprises (GIEs), with a magnitude of around 11,320 kWh on average. Second, judging from the official electricity consumption data obtained, the work resumption is quite encouraging in the sample period, with a resumption rate of 73.1%. Third, the work resumption seems to be in good condition on the surface, which also could be seen from Fig. 6 in the Appendix, while the air quality does not seem to change from good to bad, because, whether by province or not, the AQI has reached the first (good) level⁶ on average (see Table 3 in the Appendix for details). The only exception is Yunnan province, whose AQI (63.163) however is only slightly higher than the threshold of the first level. Meanwhile, detailed violin profiles of electricity consumption and AQI by province are displayed in Fig. 7 in the Appendix.

Empirical model

This paper runs fixed-effect panel regressions to test the relation between ambient air pollution and early-stage post-COVID-19 work resumption. And, industrial electricity consumption is used as a proxy measure for the post-COVID-19 work resumption. The main regression takes the following form:

$$Y_{it}^P = \beta_0^P + \beta_1^P WR_{it} + X_{it}^P + \gamma_i^P + \lambda_t^P + \epsilon_{it}^P \quad (1)$$

where i and t index province and designated day separately. The dependent variable Y_{it}^P consists of seven strands of outcomes, i.e., AQI, PM_{2.5}, PM₁₀, O₃, NO₂, and CO, which is represented by P equals 1, 2, 3, ..., 7, respectively. And, the logarithmic forms of the above seven outcome variables are used in the specifications. The independent variable WR_{it} indicates work resumption, which is defined as either the province-daily electricity consumption of enterprises (logarithm, in the baseline model) or the resumption rate (in the robustness model). X_{it}^P is a vector of controls at the province-date level, including the natural logarithm of province-day-level weather conditions (ln(WSR), ln(AT), ln(DPT), ln(SLP)) and province-month-level thermal power generation (ln(TPG)). β is the coefficient, and ϵ is the random error term. Besides, this paper takes advantage of the panel-data nature of the dataset to include province fixed effects (γ_i^P) and date fixed effects (λ_t^P) in the model specifications. These fixed effects can eliminate many potential sources of omitted-variable bias that may confound the inferences. In particular, the province fixed effects γ_i^P subsume province-specific characteristics that are time-invariant, such as economic and geographical conditions, industrial structure and policies, and environmental policies, while the date fixed effects λ_t^P absorb common shocks to all provinces on a given day.

Hence, the β_1^P is the most concerned coefficient in this paper, which captures the influence of the post-COVID-19

⁶ The classification standards of the AQI and air pollution levels are 0–50 (good), 51–100 (moderate), 101–150 (unhealthy for sensitive groups), 151–200 (unhealthy), 201–300 (very unhealthy), and > 300 (hazardous).

Fig. 2 Regression results for post-COVID-19 recovery and air quality. *Notes:* The figure shows the regression results of four various models. Specifically, Model 1 is one simple OLS model, Model 2 controls the weather conditions (including WSR, AT, DPT, and SLP), Model 3 further controls the thermal power generation, and Model 4 further controls the time trend (including the day and week trends). The unit of observation is the province-day. Sample period 03/03/2020–21/04/2020. All models have controlled the province and

day fixed effects, and the independent variables of which are all the logarithm of industrial electricity consumption. Six dependent variables are included in the plot, with different symbols. (The regression results of PM_{10} are not included because of the wider confidence interval.) The dependent and independent variables in all models are all in logarithms. The estimated coefficients and their 95% confidence intervals (error bars) are plotted. The detailed tabulated form can be available from the author

work resumption on ambient air pollution. If coefficient β_1^P is statistically significantly positive, thus, one can infer that the post-pandemic work resumption pushes up or restarts the ambient air pollution. All models in this paper are estimated via STATA 16, one of the most popular software for statistics and data science.

Overall, the comprehensive data set and empirical models in this study have two notable advantages for the analysis. First, the post-COVID-19 work resumption data is derived from the CSG and also double-checked by the CNAO's Guangzhou Resident Office, which provides enough confidence to precisely capture the post-pandemic recovery, especially in the industry sectors. Besides, electricity is a barometer of the whole economy, and all indicators in this study are based on electricity consumption. Second, the fixed-effect panel regressions allow us to control not only all unobserved province-specific time-invariant characteristics that influence the dependent variables, but also all general macroeconomic factors affecting all provinces over time.

Empirical results

This section firstly describes the results of the baseline models. Next, two various heterogeneity analyses are shown, from the perspective of enterprise-scale and sample period.

Finally, several robustness checks are performed to defend the main findings, including an alternative measure of post-pandemic recovery, an adjusted sample, two different model settings, and using the weighted average air and weather data based on city land area.

Air pollution and work resumption

The main results from the baseline empirical models corresponding to Eq. (1) for the relation between the air pollution and post-COVID-19 work resumption are depicted in Fig. 2. The dependent variable is the logarithm of seven ambient air quality indicators, i.e., AQI, $PM_{2.5}$, PM_{10} , O_3 , NO_2 , and CO, which are plotted with different symbols⁷; and the independent variable is the logarithm of industrial electricity consumption.

Surprisingly, coefficient β_1^P are all not significantly positive in the four different models, which casts doubt that there is no or weak influence of post-COVID-19 work resumption on ambient air pollution. More specifically, Model 1

⁷ It is worth noting that the regression results of PM_{10} are not included because of the wider confidence interval, and the detailed tabulated form including the results of PM_{10} can be available from the author.

in Fig. 2 presents the regression results after controlling only province and day fixed effects but not the other variables. One can find that although the coefficients for the four indicators are positive, they are statistically insignificant. Not to mention that the coefficients for the other two indicators are negative. Considering the systematically complex influence of weather conditions on ambient air pollution, Model 2 in Fig. 2 further controls four weather variables. It shows that except for NO_2 , the other five indicators all turn negative. Coal-fire power generation plays an important role in China's power system, which also affects the ambient air quality so that confusing the identification. Realized this, Model 3 in Fig. 2 further controls the province-month thermal power generation, which indicates similar results as in Model 2. Finally, given the date effects, Model 4 in Fig. 2 further controls the day and week trends, which also shows similar results as before. Combined, one cannot find a significantly positive influence of the post-COVID-19 work resumption on ambient air pollution.

Heterogeneity analysis

The scale of enterprises

With information on the electricity consumption of LIEs and GIEs in the data set, this paper can investigate the possible heterogeneous effects across differential enterprises' sizes. Panel a in Fig. 3 shows the regression results of the two subgroups, which shows that there is a positive influence between the electricity consumption of LIEs and the ambient air pollution, especially for AQI, $\text{PM}_{2.5}$, PM_{10} , and NO_2 . However, a nearly reverse effect is found in the subgroup of GIEs.

March and April

As mentioned above, the data set in this paper includes the resumption information for March and April 2020. This is because that the CNAO's Guangzhou Resident Office only collects and checks the statistical information of the 2 months. Hence, the analyses in this study are mainly intended to reveal the relation between ambient air pollution and post-pandemic work resumption in the early stage. Besides, because as time goes by, the work resumption will get better and better, so this study regresses the sample in March and April 2020 respectively. As shown in panel b in Fig. 3, from March to April 2020, the influence changes from negative to positive in general.

Robustness checks An alternative measure of post-pandemic recovery

Making full use of the data set, this study gives another regression result based on an alternative measure of the

post-pandemic work resumption, i.e., resumption rate (RR). Specifically, the RR indexes the proportion of enterprises whose electricity consumption exceeds 30% of their average daily electricity consumption in December 2019, which to some extent indicates the variation of post-pandemic recovery.

As shown in the first panel (top left) of Fig. 4, all coefficients for the six indicators are negative. Not surprisingly, one still cannot get a result supporting the null hypothesis which assumes the post-pandemic recovery causes the deterioration of air quality. That is, the main results in this subsection are generally consistent with the baseline models.

Adjusting sample

Among the provinces in the data set, Guangdong province is somewhat heterogeneous, for instance: (1) As a megacity in China, Guangdong province is more sensitive to the work resumption because of the larger proportion of the foreign population. (2) Guangdong province is located in the Guangdong-Hong Kong-Macao Greater Bay Area, with the largest economy among the provinces of the data set. (3) After the work resumption started, the pandemic in Guangdong province has rebounded to some extent, which has affected its further work resumption. Therefore, the sample excluded from Guangdong province is used to regress the baseline models again. The second panel (top right) of Fig. 4 shows the result, which still rejects the hypothesis assuming the post-pandemic recovery caused the deterioration of air quality.

Different model settings

Since the data is a long panel, the assumption of independently and identically distribution (i.i.d.) of the random error terms in the short panel thus can be relaxed. More specifically, considering the possible heteroscedasticity, intra-group autocorrelation, or inter-group simultaneous correlation in the error terms, the full feasible generalized least squares (FGLS) method is used to estimate the models again. The results are shown in the third panel (bottom left) of Fig. 4. Moreover, this study also uses the least squares dummy variable (LSDV) model to include indicator variables for each panel unit, and the results are shown in the fourth panel (bottom right) of Fig. 4. Undoubtedly, the main results of the two models are still robust enough.

Using weighted average air and weather data

In baseline models, in order to match with the province-by-day industrial electricity consumption data, the average values of city-by-day of air quality and weather data for each province are calculated. However, based on China's national

Fig. 3 Heterogeneity effect.

Notes: The figure depicts the results of two heterogeneity effects, i.e., different enterprise-scale (a) and sample period (b). All models control the weather conditions, thermal power generation, day and week trends, and the province and day fixed effects. The explanations of dependent and independent variables are the same as Fig. 2. The estimated coefficients and their 95% confidence intervals (error bars) are plotted. And, the detailed tabulated form can be available from the author

conditions, in some provinces, especially provinces with more complex geomorphological units, one may concern whether it is feasible to averagely process air quality and weather data.⁸ The concern is to some extent justified, but there is a trade-off. Since the data on the work resumption obtained from the China Southern Power Grid (CSG) is collected at the provincial level, I can only choose this sub-optimal solution. We all know that public data on air quality and weather conditions are usually a weighted average of the data collected from

monitoring stations in a particular region (usually a city). Moreover, some cities are more complex in terms of geography, so more monitoring sites are being established in these places to further enhance the data quality. Consequently, the generation of data itself is a compromise. Still, to eliminate

⁸ I would like to thank an anonymous reviewer for bringing this concern to my attention.

Fig. 4 Robustness checks. *Notes:* The figure shows four panels of robustness checks. More specifically, the first panel (top left) depicts the results of an alternative measure of post-pandemic recovery, i.e., the resumption rate. The second panel (top right) depicts the results of the adjusted sample, i.e., dropping the data of Guangdong province. The third panel (bottom left) depicts the results of the FGLS

model, while the last panel (bottom right) depicts the results of the LSDV model. All models control the weather conditions, thermal power generation, day and week trends, and the province and day fixed effects. The estimated coefficients and their 95% confidence intervals (error bars) are plotted. And, the detailed tabulated form can be available from the author

Table 2 Robustness analysis of the weighted average air and weather data based on city land area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(AQI)	ln(PM _{2.5})	ln(PM ₁₀)	ln(SO ₂)	ln(NO ₂)	ln(O ₃)	ln(CO)
ln(ELE)	-0.326 (0.315)	-0.0983 (0.319)	-2.577 (11.71)	-0.107 (0.159)	0.255 (0.205)	-0.918*** (0.327)	-0.171 (0.137)
Obs	250	250	250	250	250	250	250
Adjusted R ²	0.605	0.653	0.553	0.881	0.805	0.581	0.604

Notes: The unit of observation is the province-day. All models control the weather conditions, thermal power generation, day and week trends, and the province and day fixed effects. Accordingly, the dependent variables of models (1) to (7) are the logarithms of seven ambient air quality indicators, namely, AQI, PM_{2.5}, PM₁₀, SO₂, NO₂, O₃, and CO. In all models, the independent variable is the logarithm of industrial electricity consumption. Accordingly, the dependent variables of models 1 to 7 are the logarithms of seven ambient air quality indicators, namely, AQI, PM_{2.5}, PM₁₀, SO₂, NO₂, O₃, and CO. In all models, the independent variable is the logarithm of industrial electricity consumption.

this concern as much as possible, I add a robustness test where weighted averages of air and weather data based on city land area are used to re-estimate the baseline models. As shown in Table 2, all coefficients are not significantly positive, which are consistent with the baseline models.

Finally, another concern about the analyses is the problem of endogeneity, which may mainly come from the measurement error or missing variables. Notwithstanding that it is difficult to provide a perfectly clean causal identification, the results of the correlation are also enough.

Further discussion

Thus far, using unique official electricity consumption data of south-five provinces in China, the relation between the post-COVID-19 work resumption and the ambient air quality has been estimated. It seems counter-intuitive, however, to find no empirical support for the null hypothesis which assumes a negative relation between post-COVID-19 recovery and ambient air quality. And the results are robust enough to several robustness checks. Hence, why one cannot

find a positive relation between post-pandemic electricity consumption and ambient air pollution? And how to explain this counter-intuitive phenomenon?

Possible explanations given are as follows: First, notwithstanding that one has not observed a positive relation between the post-COVID-19 electricity consumption and the ambient air pollution in the full sample, a significantly positive relation has been found in the subgroup of LIEs as shown in the “[Heterogeneity analysis](#)” section. On the one hand, these results indicate that LIEs have undergone a remarkable recovery, which not only owing to the relatively large proportion of State-owned enterprises (SOEs) but also a powerful package of policies such as the new infrastructure, supportive electricity prices, and ensuring “six priorities” and stability in six areas and so on. On the other hand, the results also indicate that those GIEs may have not experienced a significant recovery during the study period, which may be the starting point of China’s street-stall and small-store economy. Research has been conducted on the impact of COVID-19 on specific sectors including aviation, tourism, hotels, construction, and livestock, as well as post-epidemic recovery strategies (Dimitrios et al. 2020; Dube et al. 2021; Ebekozi and Aigbavboa 2021; Garrido-Moreno et al. 2021; Jiang and Wen 2020; Strielkowski 2020; Zhuo et al. 2020). These studies, however, lack macro-strategic considerations. In this study, I argue that the first recovery of LIEs plays a crucial role in the economic recovery of countries after epidemics. This also explains why China vigorously boosted public infrastructure investment in the early post-epidemic period to stimulate economic recovery.⁹ Meanwhile, other sources of economic growth like private consumption take a backseat as pandemic-induced disruptions crippled businesses and households (Tanjangco et al. 2021). Therefore, further stabilizing and recovering the domestic market is both a challenge and a necessity for economic recovery after the epidemic (Czerny et al. 2021).

Second, from the view of time evolution, nearly all coefficients in the subgroup of April have turned positive as shown in the “[Heterogeneity analysis](#)” section, although statistically not significant. This to some extent implies that China’s domestic economy is gradually recovering over time, owing to a strong package of post-pandemic stimulating policies and also in line with one’s intuition. Economic recovery has been difficult after the epidemic due to the risk of reoccurrence and even full of twists and turns. Systematic and comprehensive thinking and consideration are needed for the post-COVID-19 economic recovery. On the one hand, while short-term stimulus policies are important, the long-term policy options taken are equally important

Fig. 5 Mechanism of stimulating post-COVID-19 recovery. *Notes:* Compiled by authors from publicly available figures. Comprehensive policies include the new infrastructure, street-stall economy, and ensuring “six priorities” and stability in six areas, etc.

(Faisal and Nirmala 2020). On the other hand, a nationally and locally integrated and coordinated policymaking ecosystem for the post-COVID-19 economic recovery is needed to be taken into account (Harris et al. 2020). Additionally, given that recovery will be slow, difficult, and long-term, policy innovation will be of particular importance (Chesbrough 2020).

Combined, these results contribute to a better understanding of the policies issued for recovery. Having reviewed China’s unique political regime and political ecology, I have then plotted the potential mechanisms that could stimulate the post-COVID-19 recovery as shown in Fig. 5.¹⁰ Under double pressure of the anti-pandemic and Sino-US trade war, China has issued a series of policies to promote post-COVID-19 work resumption, including cutting electricity prices (Ahmad et al. 2020). Because of China’s political hierarchy, the pressure is partly transferred to the local governments. Among the response manners, the local governments may assign concrete targets or indicators (e.g., targets of back-to-work and electricity consumption) to district enterprises, as well as implementing other local management decisions. In a word, China’s central and local governments have taken series of strong measures to help enterprises recover, whose effects are gradually emerging.

For other countries seeking an effective remedy to restart their economies in the post-COVID-19 era, the following policy implications are important: (i) The post-COVID-19

⁹ In March 2020, China launched “new infrastructure” projects to offset the economic impact of the COVID-19 and boost technology and sustainable development (Xinhua 2020).

¹⁰ I mainly focus on discussing the domestic impact, while international impact can refer to, e.g., Chang (2021).

work resumption is not only an economic activity but also a management behavior. It is necessary to pay attention to the effective connection between economic and management science. (ii) Pay attention to policy flexibility. The LIEs may be the breakthrough and forerunner of the post-pandemic recovery. While the policymakers should sidestep the curse of attending to one thing and losing another, i.e., taking targeted measures to help GIEs recover. (iii) One of the most effective means may be to reduce the pressure on enterprises' operating costs, such as lower electricity prices. (iv) Green stimulus packages should focus more on highly polluting and highly energy-wasting large-scale industrial enterprises, which also play an important role in coping with climate change. (v) The last point is to consider the actual national conditions. At the level of policy implementation (local government) in China, the number of LIEs is small, and almost all state-owned enterprises fall into this category, so the implementation of recovering policies is relatively easier, while the number of GIEs is larger, including many small workshops and enterprise of the service industry. Given this, on the one hand, it is relatively easier to implement the resumption policy with LIEs as the entry point, and it has a more obvious role in promoting the recovery of the overall economy; on the other hand, promoting the recovery of GIEs requires innovative policy mechanisms, such as China's specific and targeted economy policy of the street-stall and small-store. The developing countries, which are still in the developing stage and dominated by the secondary industry, are similar to China's national conditions. Therefore, this paper can provide a useful reference for their innovation of public management policies.

Conclusion and outlook

Based on a battery of studies (Dang and Trinh 2021; Khomsi et al. 2021; Wang et al. 2021), this study firstly proposes a hypothesis—controlling the impact of other

factors, post-COVID-19 work resumption has a negative effect on ambient air quality—which provides a novel perspective to reevaluate the comprehensive impact of the pandemic and also promotes the policymaking of greening the post-pandemic recovery. By using unique official electricity data of south-five provinces in China, no empirical evidence, however, is found to support this hypothesis. However, using the unique data of work resumption across provinces in China, some positive effects in different model settings even have been found. Overall, the results are robust to a series of robustness checks on the measure index, study sample, and different model settings.

However, this study provides econometric evidence that local air quality does respond to the post-COVID recovery in China, in the heterogeneous analysis. On the one hand, a statistically significant positive relation has been found in the subgroup of LIEs, which shows that the LIEs have undergone a remarkable recovery, hence maybe indicate the success of China's powerful package of stimulating policies and the wisdom of the street-stall and small-store economy. On the other hand, nearly all coefficients in the subgroup of April 2020 have turned positive, which implies that China's domestic economy is gradually recovering over time. Finally, some policy implications for other countries to recover during the post-pandemic era are provided.

Potentially fruitful areas for future research include a comparison of the effects of differential recovery policies. This includes not only different recovery policies within the same economy but also among various economies. More detailed (e.g., city- or even facility-level) and longer time-scale data can be applied to the analysis of recovery policy assessment, from the standpoint of dynamic evolution. Finally, the assessment of policies in the green recovery dimension should be given more attention.

Appendix

Table 3 Mean values of seven air quality indicators over south-five provinces in China

Province	AQI	PM _{2.5}	PM ₁₀	SO ₂	NO ₂	O ₃	CO
Guangdong	41.619	23.903	38.823	7.916	24.756	92.334	0.688
Guangxi	46.711	26.792	44.010	9.642	19.980	74.248	0.797
Guizhou	49.127	27.837	41.296	10.604	16.498	94.827	0.574
Hainan	27.204	12.435	25.898	3.231	9.102	80.074	0.519
Yunnan	63.163	37.639	55.960	8.181	17.974	123.198	0.773
Total	45.565	25.721	41.197	7.915	17.662	92.936	0.670

Notes: The table shows the mean values of the key air quality indicators over provinces in the dataset, while the population means are reported in the last row. Data source: The Ministry of Ecological Environment (MEE) and National Climate Data Center of NOAA

(a)

(b)

Fig. 6 Time trend of electricity consumption. *Notes:* Panel **a** shows the day-evolution trends of electricity consumption for Guangdong (top left), Guangxi (top right), Yunnan (middle left), Guizhou (middle right), and Hainan (bottom left). The dash blue lines in panel **a** mark the provinces' average daily electricity consumption in December 2019. Panel **b** shows the day-evolution trends of electricity consumption, further divided into large (white dots) and general (black dots) industrial enterprises, and the same provinces' order as panel **a**. Data source: The CNAO's Guangzhou Resident Office and the China Southern Power Grid (CSG). **a** Electricity consumption by province. **b** Electricity consumption by province and scale

Author contribution Yu Zheng: conceptualization, methodology, software, data curation, and writing and original draft preparation.

Data availability Not applicable.

Declarations

Ethics approval and consent to participate Not applicable.

Fig. 7 Distributions of electricity consumption and AQI. *Notes:* The figure depicts distributions of log-transformed electricity consumption (**a**) and AQI (**b**) for south-five provinces, which merge both kernel density and box plots. The inside box boundaries indicate the 25th (lower hinge) and 75th (upper hinge) percentiles; the white dots represent the median values; and the whiskers represent the upper- and lower-adjacent values, while the outside distribution clouds show the data distributions and their probability density. **a** Violin plot of electricity consumption. **b** Violin plot of AQI

Consent for publication Not applicable.

Competing interests The author declares no competing interests.

References

- Ahmad E, Stern N, Xie C (2020) From rescue to recovery: towards a post-pandemic sustainable transition for China. Working paper, China Development Research Foundation. <https://cdrf.org.cn>
- Beck F, Leger D, Cortaredona S, Verger P, Peretti-Watel P, Peretti-Watel P, Seror V, Cortaredona S, Fressard L, Launay O, Raude J, Verger P, Beck F, Legleye S, L'Haridon O, Ward J, Léger D (2021) Would we recover better sleep at the end of Covid-19? A relative improvement observed at the population level with the end of the lockdown in France. *Sleep Med* 78:115–119. <https://doi.org/10.1016/j.sleep.2020.11.029>
- Chang Y-Y (2021) The post-pandemic world: between constitutionalized and authoritarian orders – China's narrative-power play in the pandemic era. *J Chinese Polit Sci* 26:27–65. <https://doi.org/10.1007/s11366-020-09695-3>
- Chen K, Wang M, Huang C, Kinney PL, Anastas PT (2020) Air pollution reduction and mortality benefit during the COVID-19 outbreak in China. *Lancet Planet Heal* 4:e210–e212. [https://doi.org/10.1016/S2542-5196\(20\)30107-8](https://doi.org/10.1016/S2542-5196(20)30107-8)
- Chesbrough H (2020) To recover faster from Covid-19, open up: managerial implications from an open innovation perspective. *Ind Mark Manag* 88:410–413. <https://doi.org/10.1016/j.indmarman.2020.04.010>
- Clancy L, Goodman P, Sinclair H, Dockery DW (2002) Effect of air-pollution control on death rates in Dublin, Ireland: an intervention study. *Lancet* 360:1210–1214. [https://doi.org/10.1016/S0140-6736\(02\)11281-5](https://doi.org/10.1016/S0140-6736(02)11281-5)
- Collivignarelli MC, Abbà A, Bertanza G, Pedrazzani R, Ricciardi P, CarnevaleMiino M (2020) Lockdown for CoViD-2019 in Milan: what are the effects on air quality? *Sci Total Environ* 732:1–9. <https://doi.org/10.1016/j.scitotenv.2020.139280>
- Cropper ML, Simon NB, Alberini A, Arora S, Sharma PK (1997) The health benefits of air pollution control in Delhi. *Am J Agric Econ* 79:1625–1629. <https://doi.org/10.2307/1244393>
- Crossley TF, Fisher P, Low H (2021) The heterogeneous and regressive consequences of COVID-19: evidence from high quality panel data. *J Public Econ* 193:104334. <https://doi.org/10.1016/j.jpubeco.2020.104334>
- Czerny AI, Fu X, Lei Z, Oum TH (2021) Post pandemic aviation market recovery: experience and lessons from China. *J Air Transp Manag* 90:101971. <https://doi.org/10.1016/j.jairtraman.2020.101971>
- Dang HAH, Trinh TA (2021) Does the COVID-19 lockdown improve global air quality? New cross-national evidence on its unintended consequences. *J Environ Econ Manage* 105:102401. <https://doi.org/10.1016/j.jeem.2020.102401>
- Dantas G, Siciliano B, França BB, da Silva CM, Arbilla G (2020) The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro. *Brazil Sci Total Environ* 729:139085. <https://doi.org/10.1016/j.scitotenv.2020.139085>
- Dimitrios B., Christos P., Ioannis R., Vasiliadis L., 2020. Strategic management in the hotel industry: proposed strategic practices to recover from COVID-19 global crisis. *Acad. J. Interdiscip. Stud.* 9, 130. <https://doi.org/10.36941/ajis-2020-0117>
- Du X, Jin X, Zucker N, Kennedy R, Urpelainen J (2020) Transboundary air pollution from coal-fired power generation. *J Environ Manag* 270:110862. <https://doi.org/10.1016/j.jenvman.2020.110862>

- Dube K, Nhamo G, Chikodzi D (2021) COVID-19 pandemic and prospects for recovery of the global aviation industry. *J Air Transp Manag* 92:102022. <https://doi.org/10.1016/J.JAIRTRAMAN.2021.102022>
- Durante R, Guiso L, Gulino G (2021) Asocial capital: civic culture and social distancing during COVID-19. *J Public Econ* 194:104342. <https://doi.org/10.1016/j.jpubeco.2020.104342>
- Ebekozien A, Aigbavboa C (2021) COVID-19 recovery for the Nigerian construction sites: the role of the fourth industrial revolution technologies. *Sustain Cities Soc* 69:102803. <https://doi.org/10.1016/j.scs.2021.102803>
- Engzell P, Frey A, Verhagen MD (2021) Learning loss due to school closures during the COVID-19 pandemic. *Proc Natl Acad Sci U S A* 118:e2022376118. <https://doi.org/10.1073/pnas.2022376118>
- Faisal, M., Nirmala, M.P., 2020. COVID-19 and economic policy options: what should the government do? *J. Inov. Ekon.* 5.
- Garrido-Moreno A, García-Morales VJ, Martín-Rojas R (2021) Going beyond the curve: strategic measures to recover hotel activity in times of COVID-19. *Int J Hosp Manag* 96:102928. <https://doi.org/10.1016/J.IJHM.2021.102928>
- Harris JL, Sunley P, Evenhuis E, Martin R, Pike A, Harris R (2020) The Covid-19 crisis and manufacturing: how should national and local industrial strategies respond? *Local Econ* 35:403–415. <https://doi.org/10.1177/0269094220953528>
- He G, Pan Y, Tanaka T (2020) The short-term impacts of COVID-19 lockdown on urban air pollution in China. *Nat Sustain* 3:1005–1011. <https://doi.org/10.1038/s41893-020-0581-y>
- Hensvik L, Le Barbanchon T, Rathelot R (2021) Job search during the COVID-19 crisis. *J Public Econ* 194:104349. <https://doi.org/10.1016/j.jpubeco.2020.104349>
- Jiang Y, Wen J (2020) Effects of COVID-19 on hotel marketing and management: a perspective article. *Int J Contemp Hosp Manag* 32:2563–2573. <https://doi.org/10.1108/IJCHM-03-2020-0237>
- Kanniah KD, KamarulZaman NAF, Kaskaoutis DG, Latif MT (2020) COVID-19's impact on the atmospheric environment in the Southeast Asia region. *Sci Total Environ* 736:139658. <https://doi.org/10.1016/j.scitotenv.2020.139658>
- Kelsall JE, Samet JM, Zeger SL, Xu J (1997) Air pollution and mortality in Philadelphia, 1974–1988. *Am J Epidemiol* 146:750–762. <https://doi.org/10.1093/oxfordjournals.aje.a009351>
- Khomsi K, Najmi H, Amghar H, Chelhaoui Y, Souhaili Z (2021) COVID-19 national lockdown in Morocco: impacts on air quality and public health. *One Heal* 11:100200. <https://doi.org/10.1016/j.onehlt.2020.100200>
- Krawczyk K (2020) China's coronavirus recovery is “all fake,” whistleblowers and residents claim [WWW Document]. Yahoo.
- Kumar D, Singh A, Kumar V, Poyoja R, Ghosh A, Singh B (2021) COVID-19 driven changes in the air quality: a study of major cities in the Indian state of Uttar Pradesh. *Environ Pollut* 274:116512. <https://doi.org/10.1016/j.envpol.2021.116512>
- Kuo L (2020) China becomes first major economy to recover from Covid-19 pandemic. *Guard*.
- Li Y, Chiu Y, Lu LC (2018) Energy and AQI performance of 31 cities in China. *Energy Policy* 122:194–202. <https://doi.org/10.1016/j.enpol.2018.07.037>
- Liu H, Fang C, Zhang X, Wang Z, Bao C, Li F (2017) The effect of natural and anthropogenic factors on haze pollution in Chinese cities: a spatial econometrics approach. *J Clean Prod* 165:323–333. <https://doi.org/10.1016/j.jclepro.2017.07.127>
- Lu R, Zhao X, Li J, Niu P, Yang B, Wu H, Wang W, Song H, Huang B, Zhu N, Bi Y, Ma X, Zhan F, Wang L, Hu T, Zhou H, Hu Z, Zhou W, Zhao L, Chen J, Meng Y, Wang J, Lin Y, Yuan J, Xie Z, Ma J, Liu WJ, Wang D, Xu W, Holmes EC, Gao GF, Wu G, Chen W, Shi W, Tan W (2020) Genomic characterization and epidemiology of 2019 novel coronavirus: implications for virus origins and receptor binding. *Lancet* 395:565–574
- Luo H, Guan Q, Lin J, Wang Q, Yang L, Tan Z, Wang N (2020) Air pollution characteristics and human health risks in key cities of northwest China. *J Environ Manag* 269:110791. <https://doi.org/10.1016/j.jenvman.2020.110791>
- Sheehan P, Cheng E, English A, Sun F (2014) China's response to the air pollution shock. *Nat. Clim. Chang.* <https://doi.org/10.1038/nclimate2197>
- Strielkowski W (2020) International tourism and COVID-19: recovery strategies for tourism organisations. Preprints. <https://doi.org/10.20944/PREPRINTS202003.0445.V1>
- Tanjangco B, Cao Y, Nadin R, Borodyna O, Chen, Y, Calabrese L, Johnston L, Downie E (2021) Pulse 3 – recover, reform, restructure: China's outward investment appetite and implications for developing countries.
- Tong Z, Chen Y, Malkawi A, Liu Z, Freeman RB (2016) Energy saving potential of natural ventilation in China: the impact of ambient air pollution. *Appl Energy* 179:660–668. <https://doi.org/10.1016/j.apenergy.2016.07.019>
- Wang C, Horby PW, Hayden FG, Gao GF (2020) A novel coronavirus outbreak of global health concern. *Lancet* 395:470–473. [https://doi.org/10.1016/S0140-6736\(20\)30185-9](https://doi.org/10.1016/S0140-6736(20)30185-9)
- Wang J, Xu X, Wang S, He S, Li X, He P (2021) Heterogeneous effects of COVID-19 lockdown measures on air quality in Northern China. *Appl Energy* 282:116179. <https://doi.org/10.1016/j.apenergy.2020.116179>
- Xinhua (2020) Economic watch: China speeds up “new infrastructure” investment to combat economic pressure [WWW Document]. Xinhuanet. URL http://www.xinhuanet.com/english/2020-03/05/c_138846271.htm (accessed 9.2.21).
- Yuan J, Na C, Lei Q, Xiong M, Guo J, Hu Z (2018) Coal use for power generation in China. *Resour Conserv Recycl* 129:443–453. <https://doi.org/10.1016/j.resconrec.2016.03.021>
- Yuan Ruiyang IL (2020) Lights are on but no one's working: how local governments are faking coronavirus recovery [WWW Document]. Caixin. URL <https://www.caixinglobal.com/> (accessed 10.4.20).
- Yunus AP, Masago Y, Hijioka Y (2020) COVID-19 and surface water quality: improved lake water quality during the lockdown. *Sci Total Environ* 731:139012. <https://doi.org/10.1016/j.scitotenv.2020.139012>
- Zhong Q, Tao S, Ma J, Liu J, Shen H, Shen G, Guan D, Yun X, Meng W, Yu X, Cheng H, Zhu D, Wan Y, Hu J (2021) PM_{2.5} reductions in Chinese cities from 2013 to 2019 remain significant despite the inflating effects of meteorological conditions. *One Earth* 4:448–458. <https://doi.org/10.1016/j.oneear.2021.02.003>
- Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, Zhao X, Huang B, Shi W, Lu R, Niu P, Zhan F, Ma X, Wang D, Xu W, Wu G, Gao GF, Tan W (2020) A novel coronavirus from patients with pneumonia in China, 2019. *N Engl J Med* 382:727–733
- Zhuo N, Ji C, Ding J (2020) Pig farmers' willingness to recover their production under COVID-19 pandemic shock in China – empirical evidence from a farm survey. *J Integr Agric* 19:2891–2902. [https://doi.org/10.1016/S2095-3119\(20\)63411-6](https://doi.org/10.1016/S2095-3119(20)63411-6)

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.